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# BUSINESS PROCESSES OPTIMIZATION OF CONSUMER LENDING TO NON-BANK FINANCIAL INSTITUTIONS: INTEGRAL CLUSTER APPROACH TO CRM

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# ОПТИМІЗАЦІЯ БІЗНЕС-ПРОЦЕСІВ СПОЖИВЧОГО КРЕДИТУВАННЯ НЕБАНКІВСЬКИХ ФІНАНСОВИХ УСТАНОВ: ІНТЕГРАЛЬНИЙ КЛАСТЕРНИЙ ПІДХІД ДО CRM

*The article is devoted to the optimization of online lending business processes of non-bank financial institutions. Credit activity in the PDL segment (payday loans) is considered. This segment is characterized by small loan amounts, a short credit period, high credit risk and a daily interest accrual pattern. The segment does not have a high priority for banks, so it is dominated by non-banking financial institutions that build quite technological online business processes for providing loans. The authors developed the concept of integral clustering to optimize business processes in CRM (Customer Relationship Management) of online lenders of the PDL segment. The concept is based on a combination of three methodological approaches to clustering. The first approach is based on the construction of the "Whale curve", specially adapted by the authors to the analysis of the lending business in the PDL segment. The advantage of such clustering is the focus on borrowers' profitability. The second approach is an extension of the RFM (Recency, Frequency, Monetary) methodology to the case of PDL lending. The advantage of this approach is clustering based on borrowers' behavioral patterns. The third approach to clustering is based on special requests made by the creditor to the credit bureau. The system of such requests allows the identification of the potential possibility of the borrower reacting to the offer to take a loan. The proposed concept includes 24 clusters that combine different characteristics of borrowers. The result is a built-in logic of integral clustering of borrowers. This formed the basis for the optimization of CRM business processes in the direction of marketing proposals for repeated loans. The advantage of the developed concept is that it increases the effectiveness of CRM functioning of a non-banking financial institution due to the integral consideration of the behavioral characteristics of borrowers (RFM), profitability from the provision of credit, and credit risk. Digitization makes it possible to implement the proposed concept in real-time. The article illustrates the practical implementation of the concept developed by the authors.*

*Стаття присвячена оптимізації бізнес-процесів онлайн кредитування небанківських фінансових установ. Розглядається кредитна діяльність в сегменті PDL (payday loans). Даний сегмент характеризується невеликими сумами кредитів, коротким кредитним періодом, високим кредитним ризиком та патерном щоденного нарахування відсотків. Сегмент не має високого пріоритету для банків, тому в ньому домінують небанківські фінансові установи, які вибудовують досить технологічні онлайн бізнес-процеси надання кредитів. Для оптимізації бізнес-процесів в CRM (Customer Relationship Management) онлайн кредиторів PDL сегмента автори розробили концепт інтегральної кластеризації. Концепт ґрунтується на поєднанні трьох методологічних підходах до кластеризації. Перший підхід базується на побудові кривої "Whale curve", спеціально адаптованої авторами до аналізу бізнесу кредитування в PDL сегменті. Перевагою такої кластеризації є фокус на доходність позичальників. Другий підхід є розширенням методики RFM (Recency, Frequency, Monetary) на випадок PDL кредитування. Перевагою цього підходу є кластеризація на основі поведінкових зразків позичальників. Третій підхід до кластеризації заснований на здійснені кредитором спеціальних запитів до бюро кредитних історій. Система таких запитів дозволяє виявити потенційну можливість позичальника відреагувати на пропозицію взяти кредит. Запропонований концепт включає 24 кластера, які поєднують в собі різні характеристики позичальників. Результатом є вибудована логіка інтегральної кластеризації позичальників. Це склало  основу для оптимізації бізнес-процесів CRM в напрямку маркетингових пропозицій повторних кредитів. Перевагою розробленого концепту є підвищення ефективності функціонування CRM небанківської фінансової установи через інтегральне врахування поведінкових характеристик позичальників (RFM), доходності від надання кредиту, та кредитного ризику. Цифровізація дозволяє реалізувати пропонований концепт у реальному режимі часу. У статті наводиться ілюстрація практичної реалізації побудованого авторами концепту.*

***Keywords:*** *digitalization, non-banking financial institutions, consumer lending, optimization, cluster approach.*

***Ключові слова:*** *цифровізація, небанківські фінансові установи, споживче кредитування, оптимізація, кластерний підхід.*

***Statement of the problem in a general form and its connection with important scientific or practical tasks.*** The rapid development of digitalization has had a strong impact on consumer lending. Lenders, both banks and non-bank financial institutions, are actively developing online technology in lending. This affects changes in credit form, largely modifies the way of working with borrowers, creates new challenges of risk management, and opens advanced approaches to marketing and customer relationship management. Digital technologies contribute to the expansion of databases which allows the development of data mining methods and their applications. Data mining allows us to identify a wide range of patterns that can be applied in the improvement of business processes of consumer lending. Thus, it is possible to outline the explicit problem of development and application of data processing methods in business processes of consumer lending and credit risk management systems. Analysis of the problems of such issues allows to increase the economic efficiency of online consumer lending and manage credit risk within a certain “risk-return” ratio.

***Analysis of recent research and publications.*** Digitalization, technological advancements, unstable economic conditions, and regulatory amendment lead to changes in the modern financial system. The expression of these changes is the development of fintech, which is presented in [1]. It presents the results of research on the role of fintech, and, among other things, shows the perception of this development in the form of banks` threat. Fintech entered the consumer lending market about 10 years ago and is currently growing at a fast pace. This development was investigated in [2] in the light of financial stability in emerging markets.

Authors of paper [3] represent conclusions from their wide research of fintech and big tech lending development (encompassing 79 countries). The authors of this study make an interesting point that fintech and big tech credit complement other forms of credit instead of replacing them. Authors of report [4] investigated another type of fintech lending, which was realized by online platforms.

The digitalization and informatization of business processes in the context of loan approval process is considered in [5]. Authors presented some possible methods and approaches to optimization processes by supporting IT solutions. The paper [6] presents a model for optimizing correspondence risk-return-marketing for short-term lending by a non-bank financial institution. The paper [7] considers the important question of the differences between banks' information scarcity and non-bank financial settings. The article is about small firms' lending, but in our view this difference can be transferred to consumer lending.

Different data mining techniques for customer relationship management were considered deeply at the book [8]. Except for many other techniques Chapter 11 of this book reveals the automatic cluster detection issue quite deeply. Also, in terms of CRM applying data mining is considered in [9]. Authors push back from Whale curve (which is visualization of cumulative customer profitability) for forming initial clusters based on customers profitability. The paper presents the potential of neural networks as a tool in the process of analyzing and forecasting customer profitability. The advantages of neural networks in CRM are explained.

The scoring-based IT model for CRM of non-bank lenders was constructed in [10]. This article incorporates clustering of borrowers at the base of K-mean and fuzzy clustering. Clustering is also analyzed through data mining techniques in [11].

The Whale curve tools applying to the profitability analysis of fintech microlending were considered in [12]. Authors ground that identification of four borrowers' clusters at the base Whale curve is an effective tool for visualization differences in economic analysis of consumer lending for banks and non-banks.

Our research incorporates RFM (Recency, Frequency, Monetary) approach to the business process components of consumer lending. RFM is a tool for CRM which is widely described in scientific and practical literature. This tool can be used for business processes in consumer lending. It includes a few features. These features were discussed in [13]. Authors expanded RFM model to the RFM+B model (where B denotes the "Balance").

Credit bureau (bureau of credit histories) is a great source of data mining. The information in the credit bureau plays an essential role for lending institutions. At the same time running on the PDL (payday loan) market they should provide some special credit reports. These issues are discussed in paper [14].

***Formulation of the goals of the article (statement of the task).*** The goal of this article is to present the developed by the authors concept to optimizing business processes and risk management of non-bank financial institutions in the segment of PDL (payday loans) online lending. Developed concept is based on encompassing such adapted to lending tools as Whale curve, RFM (Recency, Frequency, Monetary) and extracting special data from credit bureaus for use in our development. Integral of clustering grounded on these three tools is a statement task.

***Main research evidence.*** We view the business process as a set of tasks, activities, and coordinated workflows that enable goals to be achieved. Under business process optimization we understand the increase in efficiency according to the selected indicators (KPI). The subject of our research is the business process of providing repeated loans to borrowers presented in the portfolio of non-bank financial institution, carrying out payday online lending.

Thus, as the initial object of research, we have a loan portfolio formed for a certain period, for example, a quarter. The business process involves the division of borrowers into two general types of “Good” and “Bad”. “Good” are borrowers who at the end of the quarter have completed loans without overdue. “Bad” borrowers are currently in overdue. The purpose of the business process is the proposal and issuance of a new (recurrence) loan with certain characteristics. Performance indicators of business process are portfolio income indicators, the level of repeat loans, the level of portfolio delinquency and the amount of marketing costs.

According to our approach, the optimization of the business process is carried out on the basis of the use of tools and techniques:

- Whale curve clustering.
- RFM clustering.
- Data mining of credit bureau data.

***1.Whale curve clustering***

The issuance of loans in the PDL lending system includes several features that fundamentally distinguish this system from the banking system of consumer lending. The first difference is the return generating pattern. The PDL pattern supposes daily based accrued interest. The interest rate is typically 0,5-2% per day. The second difference is the presence of complementary payments, which are a significant part of the total payments. This includes payments for prolongation of the loan, fines and penalties for delays, payment for additional services (such as buying the time break in the servicing of the loan). The third difference is the repeated loans. A great part of the credit portfolio return is generated by borrowers who take repeated loans. Analyzing the second and third differences, one can note borrowers who potentially generate significantly higher payments than others.

The fourth feature is that the PDL system demonstrates a high level of PD (Probability of Default). In particular, the reason is that short loans are taken by borrowers with low incomes. Borrowers can often take online loans simultaneously from several different lenders. This can lead to debt that exceeds the borrower's ability to repay loans. It is worth noting that the borrower in the online short-term loan segment sometimes has low motivation to repay the loan. Often the only stimulus to repay a loan is a negative record in the borrower's credit history.

The fifth feature of such lending concerns interpreting credit bureau records. Results of our study indicate that credit history data about PDL loans is very valuable for decision making.  At the same time, information about the borrower's credit history in the banking segment is less valuable than in PDL lending. Our statistical analysis proves that borrowers typically consider bank loans more responsibly than short-term ones. As a consequence, analysis of credit history dominantly should be focused to such loans.

It is necessary to note that all these elements of CRM business processes can be realizes by digital tools in real time frameworks.

Our approach to CRM business processes involves breaking borrowers (and loans) into clusters. We applied three clustering techniques and then built integral construction of clustering. The first technique is based on Whale curve, second on

RFM assessment. Third, the clustering technique is based on specific information from credit bureau.

It is necessary to note that all these elements of CRM business processes can be realizes by digital tools in real time frameworks.

The applying of Whale curve tools [12] allows us to visualize clearly the abovementioned features. High returns of borrowers with repeated loans leads to high raising of curve from the left side. A significant number of borrowers which do not pay anything leads to a dropping downward from the right side. The logic of the curve construction consists in the allocation of borrowers into 4 clusters: A, B, C, D. Cluster A represents 25% of all borrowers which are top profit makers. Cluster B encompasses all other borrowers, which provide a money stream for a lender. Cluster C includes borrowers who have returned only part of the credit amount and Cluster D includes defaulters, who did not pay any cent. Borrowers from Clusters A and B are “Good”. Borrowers from Clusters C and D are “Bad”. The typical shape of borrowers-based Whale curve is visualized in the Fig 1. The description of borrowers from different clusters is presented in Table 1.

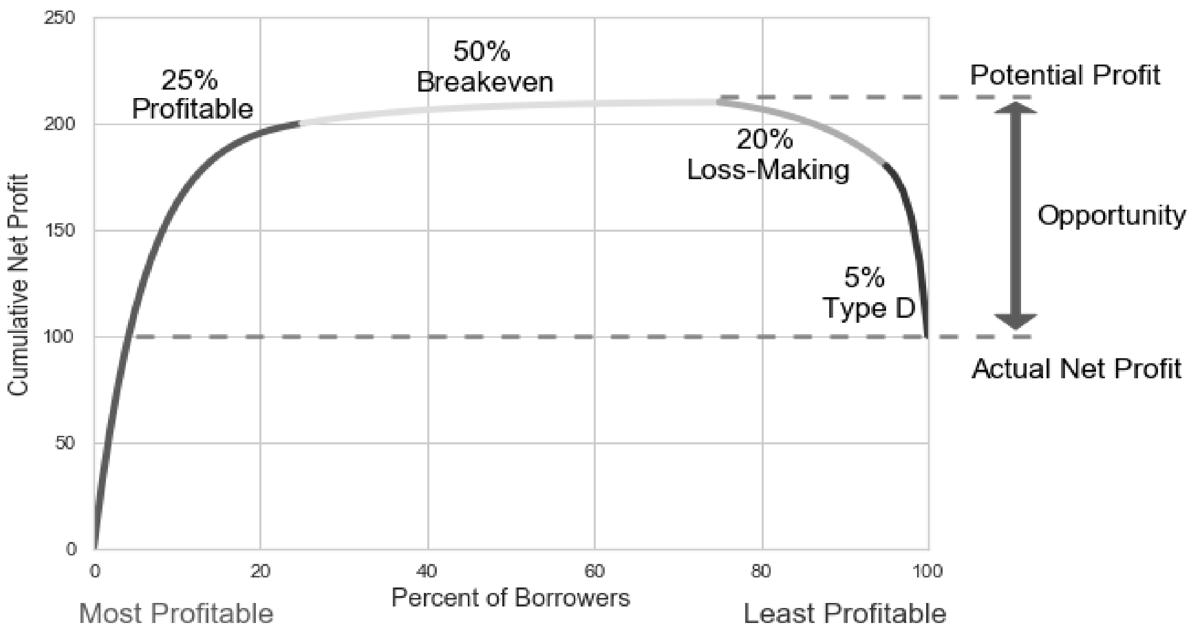


**Fig.1. Whale curve adapted to lending. Borrowers-based clustering**

Another type of Whale curve construction is based on total profit from loans, not from borrowers. Each type of Whale curve is valuable in our approach to optimization. The borrowers-based type is tied with the lead generation process.

Loan-based Whale curve is useful to effective performance analysis of loans characteristic (loan amounts, duration, default rates etc.) with the scope of issued recurrent loans.

**Table 1. Description of A, B, C, D Clusters**

| | *Borrowers-based Whale curve* | *Loans-based Whale curve* |
|---|---|---|
| *Cluster A* | 25% borrowers with higher total payments. There are 2 possible borrower types. The first type is characterized by a high money stream to lenders by different payments. The second type of borrowers embrace those who demonstrate recurrence payment rate. Borrowers from segment A raise up Whale curve. Our research shows the payments from Cluster A borrowers can be up 200%-600% compared to average payments. | 25% of loans issued is regularized by higher payments. This allows us to find the characteristics of the most profitable loans. In the section recurrence number of concrete loan. Does it first loan for some borrower? Does it recurrence loan? |
| *Cluster B* | This Cluster combines borrowers which generate profit $\geq 0$ and which are not in Cluster A. There are two types of borrowers here. The first type (it dominate) are borrowers who pay off fair and square. Second type indicates borrowers which previously paid off high, but now demonstrate last received loan as C or D. | Cluster B involves loans which generate profit $\geq 0$ and these loans are not in Cluster A. |
| *Cluster C* | Borrowers which are in partial or complete default into last loan in recurrence loan ordering. | Loans which are in partial default. The payments for these loans less than the loan amount and more than 0 (payments > 0, profit < 0). |
| *Cluster D* | Borrowers with one loan which are in total default. They do not provide any payments. | Loans in total default. There are not any payments. |

So, borrowers (or loans) from credit portfolio can be allocated to one or another Cluster: A, B, C or D. The crucial element of this clustering is the rate of return, which shows the return on each dollar issued as a loan. Clusters A, B, C, and D differ exactly by rate of return.

## 2. RFM clustering

RFM analysis is a well-known tool for marketing strategy construction. RFM analysis is based on Vilfredo Pareto principle, which postulates that 80% of business comes from 20% of the customers. RFM analysis is based on customer behavior patterns. Thus, typically customers` respond to promotion determined how recently they buy (Recency), how often they buy (Frequency), and how much they spend (Monetary).

In our study, we aimed to transfer elements of this analysis to online PDL lending. Consumers in this case are borrowers who take short loans (an analogue of buying goods). There are a number of points that confirm the admissibility (correctness) of such a transfer. Namely, PDL loan borrowers differ in the frequency of loans. Borrowers are very different by level of overpayment for the loan amount. Also, the indicator "Recency" is significant. Its interpretation can concern how the borrower is accustomed to using loans: often or not often. However, there is one fundamental difference with the classic RFM application scheme. It lies in the fact that the borrower may not repay the loan, or not fully repay. Thus, RFM analysis should be used in tandem with credit risk assessment.

In this study, we used a scoring approach to the definition of clusters of borrowers. We applied a scoring approach on a point score of 1 to 5 points. R, F, and M are scored by these numbers. Based on the scoring, we formed 6 clusters presented in Table 2. Clusters are non-intersected (constructed by sequential exclusion).

**Table 2. RFM Clusters**

| Scoring defined clusters | Explanation at the framework of score estimation with scale 1-5 |
|---|---|
| RFM 1 ("Best Borrower") | when R_score >= 4 and F_score = 5 and M_score >= 4 |
| RFM 2 ("Big Spenders") | when M_score >= 4 |
| RFM 3 ("DeadBeats") | when R_score <= 2 and F_score = 1 and M_score <= 2 |
| RFM 4 ("Lost Borrowers") | when (R_score <= 2 and F_score >= 2.5 and M_score <= 3) or (R_score <= 2 and F_ score = 1 and M_ score = 3) |
| RFM 5 ("Loyal Customers") | when F_ score = 5 |
| RFM 6 ("New Spenders") | when R_ score >= 3 and F_ score <= 2.5 |

For each RFM cluster, we investigated its profitability and risk level within the Whale curve toolkit. That is, the schedule of borrowers of each RFM cluster by clusters A, B, C, D was analyzed. RFM clusters differ in the following:

- shares of borrowers of types A, B, C, D;
- rate of returns for funds issued in the form of loans;
- retention rate.

To take this into account in CRM business processes, it is necessary to include risk management procedures in them. Because, retention rate depends not only on the disappearance of the borrower, but also his refusal because of the high current credit risk.

RFM is a good organic supplement for A, B, C, D clustering. Because RFM clusters formalize behavior, but A, B, C, D formalizes rate of return.

### 3. Credit Bureau Information clustering

Credit bureaus today are an integral element of the consumer credit market. They contain information on the characteristics of the loans taken and payments from borrowers for them. The most common approach to using credit history is to make a query to the bureau when considering a loan application (request regarding the borrower's credit history). In the case of current debt or excessive credit load, the borrower is usually rejected in loan granting. At the same time, the potential of the information contained in credit histories is quite wide. This data can be used not only for credit risk assessment, but also for marketing purposes. As part of building CRM business processes, we included the following option: to send a request to the bureau regarding the borrower before the offer to take a loan. Significant relevance was shown by indicators of the availability of recently opened loans from other lenders and requests for the borrower's credit history by other lenders. On this basis, we formed 4 clusters, which are shown in Table 3.

It is necessary to note that Table 3. involves only marketing interpretation of some indicators from credit history. Of course, other parameters for assessing credit risk should also be considered.

So, we have three clustering. The design of our approach is based on an integral approach based on the three-clustering outlined above. These clustering an their integral combination can be realized in digital form.

**Table 3. Clusters based on credit bureau information**

| Cluster | Description | Promotion activity with borrowers |
|---|---|---|
| CBI (L) | The borrower has already taken out a loan from another PDL lender | Do not make a promotional offer |
| CBI (10+) | There were more than 4 requests from various lenders in the last 10 days. The borrower has not received the loan yet | Do not make a promotional offer |
| CBI (1-4) | There were 1- 4 requests from various lenders in the last 10 days. The borrower has not received the loan yet | Provide promotional offer in active form |
| CBI (0) | There were no borrower's credit history requests in the last 10 days. The borrower has not opened loans in the PDL form. | Provide promotional offer |

## 4. Description of the business process of CRM

1. The portfolio of a non-bank financial institution that provides PDL online loans is considered. A sub-portfolio is allocated, which is formed from lending for a certain period. We used 1 quarter and 1 year time intervals in our studies. The one quarter time interval is very useful for analyzing the dynamics of the loan portfolio. Because the length of PDL credits is usually several weeks. At the same time, the one year interval is more suitable for strategic business development.
2. The Whale curve toolkit is applied for both borrowers and loans. Borrowers are clustered into clusters A, B, C, D. Also, clustering of issued loans for clusters A, B, C, D is carried out.
3. Borrowers from clusters A and B are selected and the cluster to which their last loan belongs is verified. If the last loan received belongs to clusters C or D, then such borrowers will withdraw from consideration. Further stages do not apply to them.
4. Six RFM clusters (see Table 2) are applied to borrowers from p.3. As a result, we have 12 clusters: (A, RFM1),…, (A, RFM6), (B, RFM1),…, (B, RFM6).
5. For each borrower from p.4, a request is made to the credit bureau. On this basis, borrowers are clustered into clusters CBI (L), CBI (10+), CBI (1-4), CBI (0).

6. Borrowers from CBI (L), CBI (5 +) clusters are withdrawn from consideration.
7. 24 clusters are formed through the integration of clusters p.4 and p.6.
8. To borrowers who are in 24 clusters, marketing offers are made. The costs of marketing resources are distributed at the same time in proportion to the yield shown by clusters of RFM1,..., RFM6. This yield is selected from similar clusters for the previous quarter.
9. The next application of the business process is involved after the completion of the next quarter.

The block-scheme of considered business-process is pictured in Figure 2. This scheme can be realized in digital form.

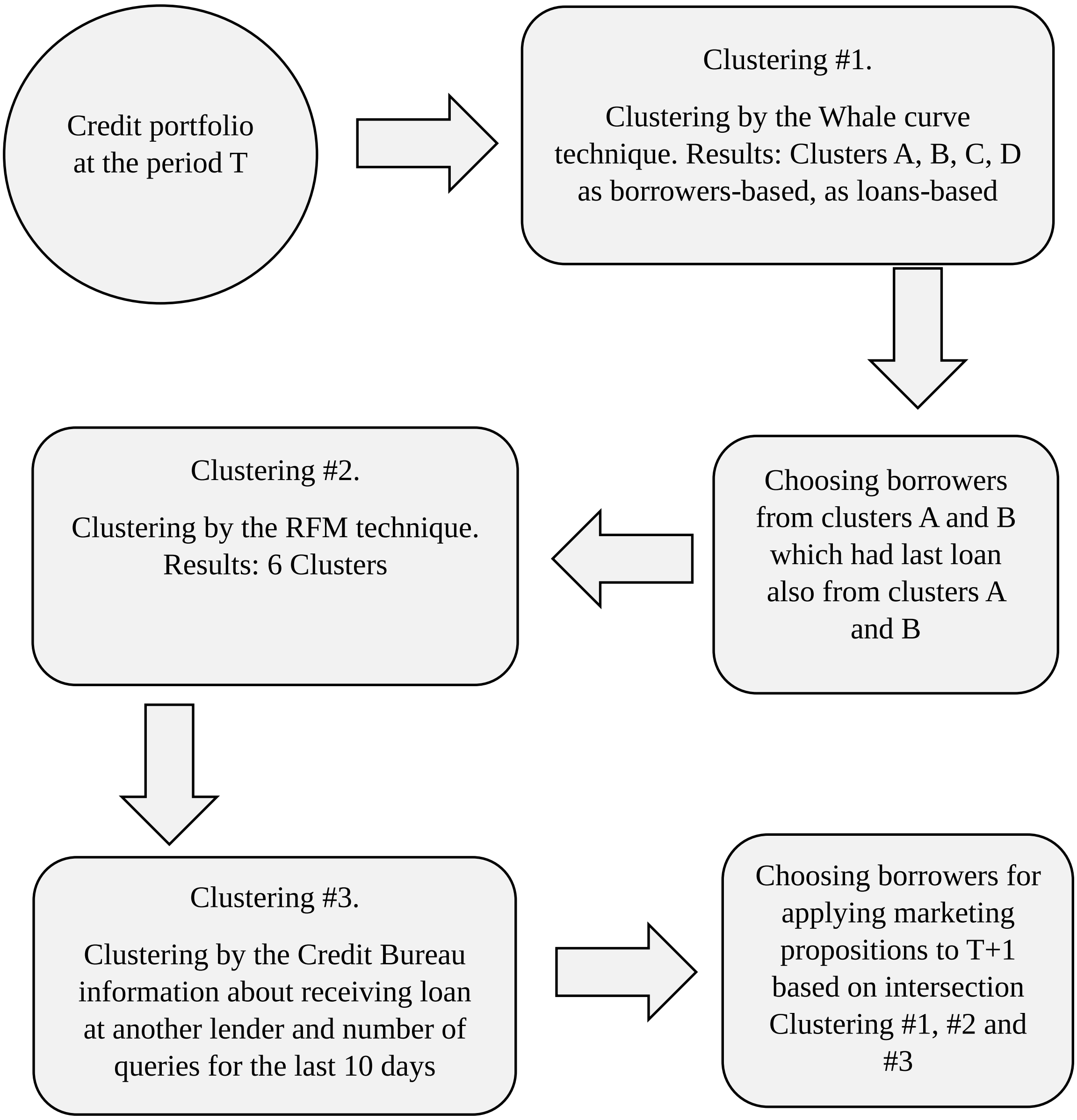


**Fig.2. Integral clustering approach to CRM**

It is necessary to make some remarks on the business process. First of all, this business process focuses on the CRM framework. At the same time, it does not exclude (but complement) the assessment of credit risk using risk management tools.  Such as client verification, application and behavioral scoring, requests to credit bureaus, etc. The second comment concerns the formation of the characteristics of the proposed loan (in particular, the amount) depending on the cluster (that is, on the specifics of each 24 clusters). This is a separate task, the research of which we will present in further publications. The third point concerns the discreteness of the application of this business process. An alternative may be to apply every day in the form of an automatic offer of a new loan to those who have completed the loan on that day (it should be absent overdue in the completed loan). However, with this approach, it is difficult to plan and control marketing budgets. In the case of a proposed discrete approach, it is possible to estimate marketing costs per client much more efficiently, depending on the resources available.

## 5. Results of practical implementation

Constructed business process was tested on loan portfolio data from one non-bank financial institution that specializes in issuing online loans on the Ukrainian market. There were used data from 2023. The basic statistics indicators of clustering and its visualization we proposed below.

The initial time interval was the 3rd quarter 2023 (denote as T). Based on the points of constructed business process, 3 clustering techniques were applied. In the first month of the T + 1 quarter, borrowers were offered loans in the amount of the last loan paid. Results of credit activity analyzed in the 2 and 3 months of the T+1 quarter. The statistical analysis was conducted on churn rate and the distribution into clusters A, B, C, D. The last allocation was calculated based on the 2 and 3 months of the T + 1 quarter. Statistical data (by RFM criteria) are given in Tables 4 and 5. From these Tables, clustering allows borrowers to be diversified according to a number of criteria, first of all by profitability (Table 5.), and by risk (Table 4.)

At the same time, Table 4. reflects two risks: credit and customer losses. Credit risk is expressed by us through C + D interest. The risk of losing a client is expressed through churn rate.

Figure 3 presents the ratio “Credit Risk – Profitability”.

The normalization values given in Table 5. show the priority of using marketing resources. The expenditure of the marketing budget can be linked with such priority.

**Table 4. Borrowers from RFM clusters distribution among A, B, C, D clusters**

| | | Distribution borrowers in the T+1 quarter | | | | |
|---|---|---|---|---|---|---|
| | RFM Clusters | Churn rate | A | B | C | D |
| Clusters on the base of portfolio in the quarter T | (A and B, RFM1) | 64% | 32% | 47% | 13% | 8% |
| | (A and B, RFM2) | 67% | 41% | 40% | 9% | 10% |
| | (A and B, RFM3) | 78% | 12% | 73% | 8% | 7% |
| | (A and B, RFM4) | 73% | 26% | 64% | 6% | 5% |
| | (A and B, RFM5) | 30% | 15% | 65% | 12% | 8% |
| | (A and B, RFM6) | 43% | 20% | 55% | 15% | 10% |

**Table 5. Economic effectiveness of lending through clusters**

| | Return+1 in the quarter T+1 (2 and 3 months) | | | | | |
|---|---|---|---|---|---|---|
| RFM Clusters | A | B | C | D | Integral by clusters | Nature Normalization |
| (A and B, RFM1) | 1,99 | 1,38 | 0,67 | 0,00 | 1,39 | 0,57 |
| (A and B, RFM2) | 2,26 | 1,35 | 0,63 | 0,00 | 1,53 | 1,00 |
| (A and B, RFM3) | 2,14 | 1,22 | 0,62 | 0,00 | 1,19 | 0,00 |
| (A and B, RFM4) | 2,25 | 1,25 | 0,72 | 0,00 | 1,35 | 0,46 |
| (A and B, RFM5) | 2,09 | 1,25 | 0,67 | 0,00 | 1,22 | 0,09 |
| (A and B, RFM6) | 2,21 | 1,27 | 0,64 | 0,00 | 1,25 | 0,18 |

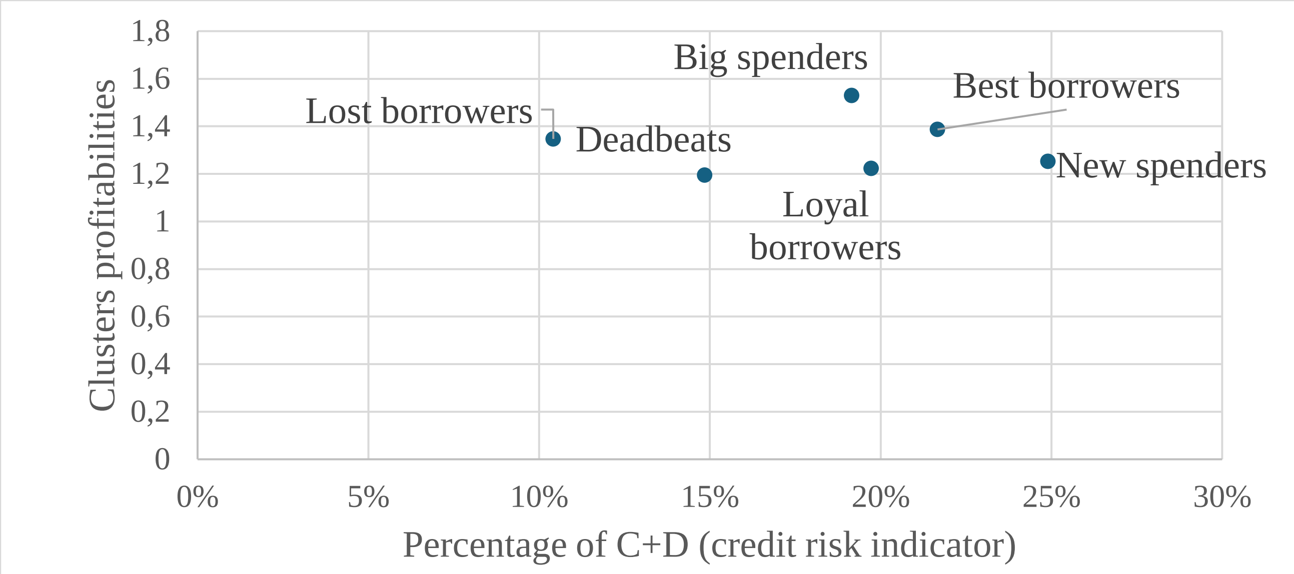


**Fig. 3. Credit risk-profitability correspondence**

***Conclusions.*** Digitalization opened up new significant opportunities in lending. This makes it possible to quite effectively introduce and develop online lending technologies, in particular, in consumer lending. In this area of lending, non-bank financial institutions show significant activity in the online PDL (payday loans) segment. This segment is characterized by small credit amounts, high default risk and a daily basis model of accrual of interest. Typically, this segment is not a priority for banks, so non-bank financial institutions dominate here and try to use digitalization to build fairly technological online business processes.

Analysis of business processes in the PDL segment shows comparability with such processes in classical CRM systems. The main comparative difference is the potential full or partial defaults of borrowers. Therefore, our paper proposed an expanded approach to CRM business processes in the PDL segment, which incorporates the risk of defaults. The proposed approach involves the integral application of three clustering techniques: based on Whale curve, on the base RFM scores, and on the base of special queries to bureau of credit histories. As a result, the logic of optimizing the business process of repeated loans promotions is built. Based on such optimization the efficiency of CRM functioning of a non-bank financial institution increases through the integral consideration of the behavioral characteristics of borrowers (RFM), the profitability of lending, and credit risk.

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